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Essays on Determinants of IPO Liquidity and Price Adjustments to Persistent Information in Option Markets

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Essays on Determinants of IPO Liquidity and Price Adjustments to Persistent Information in Option Markets

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Abstract

I examine the determinants of cross-sectional liquidity in the IPO aftermarket during the period of 1995 through 2005. I find that past price performance, the extent of stock visibility, the mass of informed agents, and certain IPO attributes play a role in explaining IPO trading activity. My empirical evidence shows that differences of opinion and estimation uncertainty about an IPO firm affect little IPO liquidity. My findings contribute to the understanding of determinants of IPO aftermarket trading. I also investigate whether contemporaneous overreaction tends to occur following persistent information in the options market. More specifically, I compare the reactions between growth and value investors, and small and large investors conditional on past price reactions. My empirical results suggest that value investors react more strongly than growth investors following a series of prior information shocks, as measured by the cumulative level of overreaction. Small investors tend to react more strongly than large investors conditional on prior information shock, as measured by the cumulative sign or level of overreaction. The results imply that overreaction is a function of investor types and previous information and contribute to the overreaction hypothesis in the options market.

Keywords: Initial public offering; Post-listing liquidity; Overreaction

Introduction

The first essay of my dissertation examines the determinants of cross-sectional liquidity in the IPO aftermarket. Previous studies focus on the factors of liquidity of seasoned stocks, whereas very few papers examine the factors of liquidity of newly-listed firms. Because IPO stocks typically experience a volatile trading period following the IPO issuance date, I draw on the literature on trading activities and IPO firms and explore the sources, if any, of IPO liquidity during the period of 1995 through 2005. I find that past price performance, the extent of stock visibility, the mass of informed agents, and certain IPO attributes play a role in explaining IPO trading activity. Previous literature suggests that differences of opinion and estimation uncertainty explain the share turnover of seasoned stocks. In contrast, I find that differences of opinion and estimation uncertainty about an IPO firm have little effect on IPO liquidity. My findings contribute to the understanding of determinants of IPO liquidity.

The second essay investigates whether contemporaneous overreaction tends to occur following persistent information in the options market. While some studies test the overreaction hypothesis for ONE index fund in the options market, I focus on the comparison between growth and value investors conditional on past price reactions. The empirical evidence suggests that value investors react more strongly than growth investors following a series of prior information shocks, as measured by the cumulative level of overreaction. Small investors tend to react more strongly than large investors conditional on prior information shock, as measured by the cumulative sign or level of overreaction. The results imply that overreaction is a function of investor types and previous information. The results provide additional evidence on the complex behavior of investors and suggest that value and growth investors react differently to information.

Chapter 1: The Determinants of Cross-Sectional Liquidity in the IPO Aftermarket

Introduction

This paper aims to study the cross-sectional variations in trading activity after firms undertake Initial Public Offerings (IPOs). To the author's knowledge, there exits no comprehensive study on factors affecting liquidity of newly IPO firms. What can be inferred from previous research is that the months following the IPO offer date is a period of high trading activity (e.g., Ellis, Michaely, and O'Hara (2002) and Corwin, Harris and Lipson (2004)). The reasons for the high trading activity, however, are not clear. In this study, I draw on the literature of trading volume and IPO to analyze the determinants of IPO liquidity. In short, I hypothesize that the amount of uninformed trading, the extent of uncertainty, dispersion of opinion, and IPO attributes explain the level of IPO liquidity. The results of this study could enhance our understanding of the determinants of liquidity, particularly of the newly-listed stocks. That is, the results may shed lights on the nature of IPO firms. Indeed, my empirical results indicate that the relative importance of several explanatory variables differ between the first half and second half year after the IPO issuance date. Moreover, I analyze three dimensions of liquidity: relative bid-ask spread, share turnover, and price impact. The panel regression results sometimes differ among three liquidity measures, suggesting the relevance of examining various aspects of liquidity.

Empirical research documents a noteworthy difference of liquidity between IPO and seasoned stocks. For example, Hedge and Miller (1989) find a significant difference in the bid-ask spreads between IPOs and seasoned stocks. The spreads of IPO stocks are, on average, about three-fourths as large as those of seasoned stocks. Liquidity is important for IPO stocks, because a liquid market reduces the transaction cost and lowers trading volatility. Despite the importance of liquidity in the IPO aftermarket, little research has examined the determinants of liquidity in the secondary market for IPO stocks.

Given the fact that newly listed firms have no prior trading history and little publicly available information, I conjecture that IPO structure and visibility play a role in their higher trading activity. A great deal of finance literature has studied the IPO characteristics, such as short-term underpricing, price stabilization, venture capital backing, lockup period, and the role of investment banks. Some of the literature suggests that IPO characteristics have an impact on trading activities. For example, Field and Hanka (2001) find a permanent 40 percent increase in average trading volume following the expiration of lockup periods, during which insider selling is prohibited. They also document that the trading volume is larger when the IPO firm is financed by venture capital. Nonetheless, there is no comprehensive analysis to examine the relationship between these characteristics and liquidity in the IPO aftermarket.

The most related study is Chordia, Huh, and Subrahmanyam (2007), who demonstrate that uninformed trading, the extent of uncertainty, and dispersion of opinion have a significant impact on monthly turnover. They examine determinants of turnover for seasoned stocks. In contrast, I analyze IPO stocks. In so doing, I utilize both IPO and market microstructure literature to identify factors that may affect IPO liquidity. My main contributions therefore come from the development of factors that affect IPO trading. Moreover, I examine three aspects in liquidity, namely, relative bid-ask spreads, trading intensity, and price impacts, whereas Chordia, Huh, and Subrahmanyam (2007) look at only turnover that captures only one dimension of liquidity. Again, the empirical results differ among the three measures.

I run random effects models of IPO liquidity on a broad set of explanatory variables. Past return and return volatility form proxies for past price performance. I use firm size and price as proxies for a firm's visibility. The mass of informed agents is proxied by the number of analysts following an IPO stock. Forecast dispersion and financial leverage reflect the degree of differences of opinion and relative earnings surprises proxy for the extent of uncertainty about an IPO stock. I also examine IPO attributes including the presence of venture capital, the number of underwriters in a syndicate, and a dummy that represents hot/cold IPO market. The empirical evidence indicates that post-IPO trading activity depends on past price performance, stock visibility, informed agents, and certain IPO attributes. I find little evidence for differences of opinion and estimation uncertainty being important. As a robustness check, I address potential endogeneity problems by running random effects regressions of IPO liquidity on one-month lagged explanatory variables. The results largely confirm the importance of liquidity trading, the mass of informed agents, as well as particular IPO characteristics.

The remaining sections of this essay are organized as follows. The next section reviews the related literature. Section 3 explains hypotheses and the choice of proxies. Section 4 describes the data and summary statistics. I discuss the empirical results in Section 5 and address the possible endogeneity problems in Section 6. The last section concludes.

Literature Review

I first review the literature on IPO characteristics, which are expected to be relevant to the trading activity of IPO stocks. This is followed by the literature on the determinants of the liquidity of seasoned stocks, including uninformed trading, the extent of uncertainty, and dispersion of opinion.

IPO Characteristics

A great deal of literature on IPO has examined unique IPO characteristics, including short-term underpricing, price stabilization, investment banks, and venture capital backing. Boehmer and Fishe (2000) suggest that underwriters create active aftermarket trading by underpricing IPOs. Fishe (2002) shows that stock flippers have the greatest effect on pricing in weak IPOs, compared to hot IPOs.[1] Those findings suggest that both underwriters and market participants generate liquidity in the post-issuance trading of newly traded securities.

Price stabilization that underwriters carry out in a short period (typically within 30 days) after the offering can also affect liquidity. If the stock price in the secondary market falls below the offer price, the lead manager may decide that the members of the syndicate need to stabilize the trading price. Price stabilization usually involves the combined use of aftermarket purchases, penalty bids[2], short position, and overallotment option.[3] Prabhala and Puri (1998) argue that underwriters stabilizing IPOs create liquidity in the aftermarket. Aggarwal (2000) shows that underwriters stimulate demand through short covering and overallotment option. Investment banks also restrict supply of IPO shares by penalty bids. Fishe (2002) theoretically demonstrates that in certain states, it may be optimal for an underwriter to exercise overallotment option. Those studies point out that the underwriters engaging in price stabilization play a role in the IPO aftermarket liquidity by managing both supply and demand of IPO shares.

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[1] Stock flippers refer to the buyers of IPO shares who sell IPO shares in the secondary market in a few days following IPO offer date. Although stock flippers usually increase the trading volume of IPO firms, they may cause the trading price of IPO shares to decline.

[2] Penalty bids refer to the forfeiture of selling concession by a lead manager of an underwritten syndicate. Members of a syndicate that distribute IPO shares receive compensation or selling concession from a lead manager. If the clienteles of distributing members sell their shares in a few days after the offering date (i.e., flipping shares), the lead manager of a syndicate may penalize those distributing members by forfeiting all or part of the selling concession as penalty bids.

[3] Overallotment option usually allows underwriters to buy additional 15 percentage of the number of issuance shares from issuing firms in a certain period after the offering date. As a result, the exercise of overallotment option by investment bankers tends to increase the supply of IPO shares in the secondary market.

Other potentially important factors for IPO aftermarket are the ranking of investment banks and the presence of venture capital. Prestigious underwriters tend to market only IPOs of high-quality firms. Carter and Manaster (1990) find a significant negative relationship between the level of prestige and the magnitude of underpricing. Ellis, Michaely, and O'Hara (2000) rank investment banks by their market share on the basis of average deal size and number of IPOs underwritten (see Table III in their paper for the ranking). Wang and Yung (2008) find that reputable investment banks resolve a greater degree of uncertainty in an IPO, because those reputable underwriters are associated with more active filing price revisions and less secondary market return variability. Previous studies show that the involvement of venture capital is vital in IPO returns and liquidity. Brav and Gompers (1997) find that venture-backed IPOs outperform non-venture-backed IPOs using equal weighted returns. Moreover, Gompers and Lerner (1998) indicate that venture capitalists use inside information to time stock distributions. As a consequence, venture capitalists are able to influence the IPO liquidity by means of deliberately timing the market.

Uninformed Trading

Kyle (1985) and Admati and Pfeiderer (1988) theorize that trading results from interaction of informed trader and uninformed traders (uninformed traders are sometimes referred to as liquidity traders). Chordia, Huh, and Subrahmanyam (2007) show that uninformed trading measured by stock visibility and past returns explains a large portion of cross-sectional variations in the monthly turnover for a comprehensive sample of NYSE/AMEX and Nasdaq stocks.

Extent of Uncertainty

The extent of uncertainty affects the level of liquidity. Other things being equal, a higher degree of uncertainty motivates investor to trade and increases trading volume. Corwin, Harris, and Lipson (2004) find that uncertainty influences initial IPO liquidity. Initial buy-order is higher for IPO stocks with less uncertainty, and vice versa. Cao, Ghysels, and Hatheway (2000) and Aggarwal and Conroy (2002) suggest that market makers reduce the extent of uncertainty pertinent to price and volume by revising bid-ask quotes during the preopening period on the first day of trading.[4] Ziebart (1990) documents that trading activity is positively associated with the absolute value of earnings surprises, which proxies for the extent of uncertainty. In their theoretical model, Ellul and Pagano (2006) demonstrate that investors who buy IPO shares take into account the extent of uncertainty measured by the expected after-market liquidity and liquidity risk.

Dispersion of Opinion

Varian (1989) and Harris and Raviv (1993) theorize that assets with more dispersion of opinion will have more trading volume in the framework of Arrow-Debreu equilibrium. Ofek and Richardson (2003) find a positive relationship between the IPO underpricing and heterogeneous beliefs among investors for Internet stocks. Boehmer and Fishe (2000) indicate that pessimistic investors flip shares to optimistic investors in the IPO aftermarket, since pessimistic investors have lower valuation regarding IPO stocks than optimistic investors. In short, the theoretical models and empirical studies indicate that dispersion of opinion among traders lead to higher liquidity.

[4] Admati and Pfleiderer (1988) theoretically suggest such actions.

Hypotheses and Variables

Other things being equal, liquidity rises as estimation uncertainty about fundamental value increase. Relative absolute earnings surprises (*RAES*) form a proxy for post-issuance estimation uncertainty about a stock and is calculated as the earnings surprises (actual earnings minus forecast earnings) divided by forecast earnings. Information-based trading activity depends on the extent of information production. I conjecture that the number of informed agents (*LANA*) is positively linked to informed trading, where *LANA* is defined as the log of one plus the number of analysts following IPO stocks.

Stock visibility and past price performance contribute to liquidity or noise trading. The theoretical model of Merton (1987) suggests that stock visibility draws the attention of individual investors in market equilibrium with incomplete information. To proxy for stock visibility, I consider the measures of stock price, firm size, and book-to-market ratio. The stock price and firm size are calculated as the log of price (*LSP*) and market value of equity (*LMV*), respectively. The book-to-market ratio (*BM*) is estimated as the shareholders' equity divided by the market value of equity. I hypothesize that the IPO firms associated with higher stock prices, larger firm size, or lower book-to-market ratios are more likely to experience more uninformed trading.

The higher is the past return, the more is the informationless trading triggered by portfolio rebalancing needs in the IPO aftermarket. In particular, the well-know short-term underpricing is expected to considerably increase liquidity or noise trading for IPO stocks. On account of the possible impact of short-selling constraints on trading, following Chordia et al. (2007), past return is separated by up and down market into positive past return (*RET+*) and negative past return (*RET−*). *RET+* and *RET−* are defined as the lagged one-month positive and negative return, respectively, and zero otherwise. Gomes (2005) theorizes a model of portfolio choice and stock trading volume and suggests a positive correlation between trading volume and stock return volatility. In addition to the level of past return, I incorporate the volatility of price return (*SDPR*)[5], defined as the standard deviation of present daily returns, to account for liquidity or noise trading.

Based on the theoretical model of Varian (1895, 1989), I hypothesize that a higher level of differences of opinion will result in more trading activity, given that investors possess the same information but interpret it in a different way. Analyst forecast dispersions (*FD*) and firm leverage (*LE*) proxy for the heterogeneity of opinion. In light of Diether, Malloy, and Scherbina (2002), the analyst forecast dispersion is defined as the standard deviation of earnings per share forecasts of multiple analysts. Agency problem implies that divergence of opinion and risk that investors perceive are larger in a firm with excessive debt. The firm leverage is defined as the ratio of book debt to total asset, where book debt is the sum of current liabilities and long-term debt.

IPO characteristics could affect liquidity. The venture capital and underwriters in a syndicate presumably disseminate information of IPO securities. The greater the number of venture capital (*VCD*) and the number of underwriters (*NMM*) involved in an IPO syndicate are supposed to cause higher trading activity due to possibly less information asymmetry in the secondary market.[6] *VCD* is equal to one if a venture capital fund involves in an IPO and zero otherwise, and *NMM* is the number of underwriters in a syndicate, including lead manager, co-managers, and members of the syndicate who are responsible for the distribution and sales of the

[5] On the other hand, investors may perceive the volatility of past price performance as uncertainty about fundamental values, thereby leading to higher trading activity.
[6] One may contend that the involvement of venture capital or a larger number of underwriters enhances the visibility of an IPO stock, thereby improving aftermarket liquidity.

underwritten shares. The underwriters serve as a source of uninformed trading when they exercise overallotment option for the purpose of stabilizing IPO price. The ratio of shares exercised in overallotment option to total shares outstanding (*ROS*) should be positively associated with the IPO aftermarket liquidity over a price-stabilization period. Arguably, a larger indicative price range results in higher IPO aftermarket liquidity. This is because the indicative price range may reveal the pre-issuance estimation uncertainty with regard to intrinsic value (see Kandel, Sarig, and Wohl (1999), and Cornelli and Goldreich (2003)), or differences of opinion. Higher indicative offer price (*IPR*) is assumed to increase post-IPO trading activity. *IPR* is derived by subtracting low filing price from high filing price documented in an IPO prospectus.

Both industry learning and structural break effects could influence the IPO aftermarket liquidity. The industry learning effects resulted from the spillovers of information production in a specific sector may trigger informed trading, as Benveniste, Ljungqvist, Wilhelm, and Yu (2003) suggested that investment banks implicitly bundle offerings to prevent failures in primary equity markets. To reflect the nature of industry learning effects, I proxy the number of IPOs in the same industry (*NIH*) for the industry learning effects on IPO liquidity. The more IPOs in the same industry is observed, the more likely it is to cause informed trading. *NIH* is calculated as the number of IPOs with the same four-digit SIC code half year prior to IPO offer date. To check for the possible structural break effects of hot and cold IPO periods on IPO trading activity, I use hot IPO dummy (*HID*) to distinguish a hot IPO period from a cold IPO period.[7] *HID* takes on the

[7] Benveniste, Ljungqvist, Wilhelm, and Yu (2003) examine the effects of information spillovers on IPO issues and use the number of filings in active registration on a firm's offering date to proxy hot issue market. Lowry and Schwert (2002) show the fluctuation of IPO issues at the monthly frequency from 1960 to 2001 in Figure 1 and conclude that more positive information lead to more companies filing IPOs. Ritter and Welch (2002) indicate year-by-year variations in the number of IPOs and aggrate gross proceeds from 1980 to 2001 in Table 1.

value of one if the number of IPOs in a year is greater than the average number of IPOs during the sample period and zero otherwise.

Finally, I measure IPO trading activity in three aspects, namely, relative bid-ask spreads, share turnover, and price impact. Lo and Wang (2000) argue that share turnover is an appropriate measure of trading activity. I add relative bid-ask spreads[8] to represent transaction costs instituted by market makers, and price impact that evaluates the impact of trading on prices, computed as the absolute price change relative to the amount of shares traded. The consideration of relative bid-ask spreads and price impact as dependent variables takes a step toward understanding IPO trading activity from different viewpoints. Relative bid-ask spreads (*RAB*) are defined as the difference of ask and bid price divided by the midpoint of ask and bid price. The share turnover (*TURN*) is the number of traded shares divided by the total number of shares outstanding. The price impact (*PI*) is calculated as the absolute of price change divided by the number of traded shares. The next section explains the sample data and descriptive statistics.

Data and Descriptive Statistics

I identify U.S. IPOs listed on the NYSE, AMEX, and NASDAQ from January 1995 to December 2005 from Securities Data Corporation (SDC) New Issues database. The IPO sample excludes withdrawn IPOs, unit offers, closed-end funds, REITs, and ADRs. I collect monthly data for each IPO stock one year following IPO issuance date, except for the first month. The data of the first month subsequent to IPO issuance date is not included because I use one-month lag of return as one of the explanatory variables. Moreover, the first month's trading is affected

[8] Roll (1984) suggests that effective bid-ask spread be measured by $2\sqrt{-Cov}$ where *Cov* is the first-order serial covariance of price changes under the assumption of market efficiency.

by investment bank's stabilization and the lack of analyst coverage, which implies that the first month's trading is abnormal. In order to examine whether IPO liquidity behaves differently between the second and twelfth month after the issuance date, I split the entire IPO sample into two periods. The first period (interchangeably, period 1) represents the dataset during the period of the second month to sixth month, while the second period (interchangeably, the period 2) constitutes the dataset during the period of the seventh month to twelfth month. The sixth month cutoff point coincides with the typical expiration of lockup period. This is important because it means that the second period is more likely to reflect the activity of a "normal" firm.

Three different measures of IPO liquidity come from Center for Research in Securities Price (CRSP), including relative bid-ask spreads, turnover, and price impact. CRSP also provides the data for past return (*RET*+ and *RET*−), volatility of present return (*SDPR*), firm size (*LMV*), and stock price (*LSP*). Using the book debt and shareholders' equity in COMPUSTAT and equity value in CRSP, I obtain leverage (*LE*) and book-to-market ratio (*BM*). IBES database offers analyst forecast dispersion (*FD*) and relative absolute earnings surprises (*RAES*). The source of variables pertinent to IPO characteristics, such as *IPR*, *ROS*, *NMM*, *VCD*, *NIH*, and *HID,* is the Global New Issues Database of Securities Data Company (SDC). The original sample dataset consists of 20,652 firm-month observations. I exclude missing data mostly because *FD* and *RAES* are not available for many newly listed firms.[9] The final entire IPO sample comprises12,152 firm-month observations, with the first and second periods containing 4,978, and 7,174 firm-month observations, respectively.

[9] Since IBES database yields earnings forecast on a quarterly basis, it is difficult to substitute either previous or subsequent values for missing earnings forecast within only one-year horizon.

Table 1 summarizes descriptive statistics for the three measures of liquidity and explanatory variables. At a first glance, the statistics for each of liquidity measures are quite similar for periods 1, and 2. Panel A indicates that newly listed firms tend to be growth stocks and equity-financed because the average of book-to market ratio and leverage are 0.41 and 0.39, respectively. Most of IPO stocks involve the sales of additional shares in the secondary market because the average ratio of shares exercised in overallotment option to total shares outstanding is 0.13, very close to 15 percent of which investment banks typically take a short position in a new issuance. There appear to no huge difference between periods 1 and 2. Not reported in Table 1, the hot IPO period is found to be the horizon from year 1995 through 2000 because the number of IPOs in each year of this period is higher than the average number of IPOs from 1995 to 2005. The cold period is found to be from year 2001 to 2005, consistent with the anecdotal collapse of internet bubble beginning in 2001.

Table 2 presents the correlation matrix of explanatory variables. As expected, the series of the log of market value (*LMV*) and stock price (*LSP*) are positively correlated. Moreover, *LMV* is positively correlated with the number of underwriters (*NMM*) in a syndicate and the number of analysts (*LANA*), suggesting that larger IPO firms are related to more underwriters and security analysts. Because the explanatory variables are not strongly correlated, the bias owning to multicollinearity in the regression models should not be of major concern.[10] I also address the possible endogeneity problems between trading activity and independent variables in Section 6.

[10] A large sample size (12,152 firm-month observations) may mitigate multicollinearity problems and produce more precise parameter estimates with lower standard errors.

Table 1
Descriptive Statistics

This table summarizes descriptive statistics for the full period, containing the monthly data of IPO firms from 1995 to 2005. The relative bid-ask spread (*RAB*) is defined as the difference of ask and bid price divided by the midpoint of ask and bid price. The turnover (*TURN*) is defined the number of traded shares divided by the total number of shares outstanding. The price impact (*PI*: dollars in 1000 shares) is measured as the absolute of price change divided by 1000 traded shares. The past returns, *RET+* and *RET−*, are the positive and negative return at a month lag, respectively, and zero otherwise. *SDPR* is volatility of present daily return in each month. The stock price and firm size are computed as the log of price (*LSP*) and equity value (*LMV*), respectively. The book-to-market ratio (*BM*) is estimated as the shareholders' equity divided by the market value of equity. *LANA* is defined as the log of one plus the number of analysts following IPO stocks. Forecast dispersion (*FD*) is the standard deviation of quarterly analyst earnings forecast reported in dollars per share in the IBES database. Leverage (*LE*) is the book debt divided by market equity value. *RAES* is calculated as the earnings surprise (actual earnings minus forecast earnings) divided by forecast earnings. IPR is derived by subtracting low filing price from high filing price documented in an IPO prospectus. *ROS* is the ratio of shares exercised in overallotment option to total shares outstanding. *NMM* is the number of underwriters in a syndicate and *VCD* is equal to one if a venture capital fund involves in an IPO firm and zero otherwise. *NIH* is calculated as the number of IPOs with the same four-digit SIC code half year prior to IPO offer date. Hot IPO dummy (*HID*) takes on one if the number of IPOs in a year is greater than the average number of IPOs during the sample period and zero otherwise.

Panel A		**Full period**				
Category		Mean	Median	STD	Skewness	Kurtosis
Liquidity	*RAB*	0.02	0.01	0.02	1.91	6.48
	TURN	0.16	0.10	0.23	7.59	127.80
	PI	0.02	0.01	0.06	10.56	185.95
Price performance	*RET+*	0.09	0.01	0.16	3.02	14.50
	RET−	-0.08	0.00	0.15	-3.10	13.90
	SDPR	0.21	0.17	0.13	2.32	19.39
Stock visibility	*LMV*	5.87	5.82	1.20	0.40	0.28
	LSP	2.74	2.80	0.72	-0.41	0.79
	BM	0.41	0.29	0.53	9.73	196.40
Informed	*LANA*	1.49	1.39	0.37	0.94	0.57
Dispersion of opinion	*FD*	0.03	0.01	0.25	36.07	1,560.26
	LE	0.39	0.30	0.31	4.89	93.03
Uncertainty	*RAES*	0.60	0.21	1.59	9.64	136.69
Pre-IPO uncertainty	*IPR*	2.01	2.00	0.61	4.07	62.65
	ROS	0.13	0.15	0.03	-2.07	3.84
	NMM	3.54	3.00	1.80	3.86	27.37
	VCD	0.55	1.00	0.50	-0.21	-1.96
IPO cycle	*NIH*	8.28	3.00	13.35	2.30	4.60
	HID	0.71	1.00	0.45	-0.94	-1.12

Observations (firm-month) = 12,152

Table 1
Descriptive Statistics (continued)

This table summarizes monthly descriptive statistics for the period 1, which represents the dataset during the period of the second month to sixth month after the issuance date.

Panel B		**Period 1**				
Category		Mean	Median	STD	Skewness	Kurtosis
Liquidity	*RAB*	0.02	0.01	0.01	1.70	4.71
	TURN	0.15	0.10	0.22	6.69	76.83
	PI	0.02	0.01	0.05	8.03	105.05
Price performance	*RET+*	0.11	0.02	0.18	2.82	11.07
	RET−	-0.08	0.00	0.15	-3.35	17.18
	SDPR	0.22	0.18	0.14	1.71	5.29
Stock visibility	*LMV*	5.95	5.90	1.17	0.43	0.25
	LSP	2.82	2.84	0.67	-0.17	0.88
	BM	0.36	0.25	0.47	9.70	211.99
Informed	*LANA*	1.41	1.39	0.32	1.10	1.23
Dispersion of opinion	*FD*	0.02	0.01	0.13	34.20	1,378.72
	LE	0.39	0.28	0.35	7.20	133.19
Uncertainty	*RAES*	0.60	0.23	1.48	9.22	126.30
Pre-IPO uncertainty	*IPR*	2.02	2.00	0.60	4.48	66.78
	ROS	0.13	0.15	0.03	-2.05	3.76
	NMM	3.59	3.00	1.77	3.70	24.39
	VCD	0.57	1.00	0.50	-0.28	-1.92
IPO cycle	*NIH*	8.49	3.00	13.78	2.28	4.41
	HID	0.75	1.00	0.43	-1.13	-0.71

Observations (firm-month) =4,978

Table 1
Descriptive Statistics (continued)

This table summarizes monthly descriptive statistics for the period 2, which represents the dataset during the period of the seventh to twelfth month after the issuance date.

Panel C		**Period 2**				
Category		Mean	Median	STD	Skewness	Kurtosis
Liquidity	*RAB*	0.02	0.01	0.02	1.95	6.69
	TURN	0.17	0.11	0.24	8.06	151.35
	PI	0.02	0.01	0.07	10.52	174.47
Price performance	*RET+*	0.09	0.01	0.15	3.13	17.93
	RET−	-0.08	0.00	0.14	-2.93	11.58
	SDPR	0.20	0.17	0.13	2.80	31.47
Stock visibility	*LMV*	5.82	5.77	1.22	0.39	0.30
	LSP	2.69	2.77	0.74	-0.50	0.61
	BM	0.45	0.32	0.57	9.68	186.04
Informed	*LANA*	1.55	1.39	0.40	0.78	0.14
Dispersion of opinion	*FD*	0.03	0.01	0.31	31.14	1,126.26
	LE	0.39	0.31	0.28	1.35	5.40
Uncertainty	*RAES*	0.60	0.20	1.66	9.80	139.10
Pre-IPO uncertainty	*IPR*	2.00	2.00	0.62	3.82	60.08
	ROS	0.13	0.15	0.03	-2.08	3.90
	NMM	3.50	3.00	1.82	3.97	29.30
	VCD	0.54	1.00	0.50	-0.15	-1.98
IPO cycle	*NIH*	8.13	3.00	13.05	2.31	4.71
	HID	0.69	1.00	0.46	-0.82	-1.34

Observations (firm-month) =7,174

Table 2
Correlation Matrix

This table presents the correlation matrix of explanatory variables for the **full period** that contains the monthly data of IPO firms from 1995 to 2005. The asterisk highlights correlation coefficients if greater than 0.3 or less than -0.3. The total number of firm-month observations is 12,152.

	RET+	*RET−*	*SDPR*	*LMV*	*LSP*	*BM*	*LANA*	*FD*	*LE*	*RAES*	*IPR*	*ROS*	*NMM*	*VCD*	*NIH*	*HID*
RET+	1															
RET−	0.32*	1														
SDPR	0.12	-0.37*	1													
LMV	0.14	0.10	-0.02	1												
LSP	0.18	0.19	-0.08	0.66*	1											
BM	-0.13	-0.06	-0.08	-0.22	-0.21	1										
LANA	0.00	-0.01	-0.01	0.52*	0.27	0.00	1									
FD	-0.01	-0.02	0.01	-0.02	-0.01	0.04	0.00	1								
LE	-0.08	0.13	-0.28	0.11	0.01	0.01	0.07	0.02	1							
RAES	0.00	-0.05	0.07	-0.05	-0.05	0.01	-0.05	0.02	-0.01	1						
IPR	-0.01	0.01	-0.02	0.22	0.08	0.00	0.13	0.01	0.07	0.01	1					
ROS	-0.03	-0.01	-0.02	-0.10	0.03	-0.14	-0.07	0.02	-0.10	0.02	-0.08	1				
NMM	-0.05	0.05	-0.16	0.49*	0.19	0.18	0.47*	0.02	0.23	-0.02	0.14	-0.12	1			
VCD	0.07	-0.10	0.23	0.08	-0.02	-0.16	0.10	0.02	-0.20	0.01	-0.02	0.05	0.00	1		
NIH	0.12	-0.14	0.34*	0.03	0.03	-0.11	-0.03	-0.01	-0.25	0.03	-0.01	0.02	-0.10	0.20	1	
HID	0.08	-0.08	0.23	-0.18	0.02	-0.09	-0.28	0.01	-0.12	0.03	0.01	-0.03	-0.42*	-0.15	0.22	1

Table 2
Correlation Matrix (continued)

This table presents the correlation matrix of explanatory variables for the **first period** that contains the monthly data of IPO firms from 1995 to 2005. The asterisk highlights correlation coefficients if greater than 0.3 or less than -0.3. The total number of firm-month observations is 4,978.

	RET+	*RET−*	*SDPR*	*LMV*	*LSP*	*BM*	*LANA*	*FD*	*LE*	*RAES*	*IPR*	*ROS*	*NMM*	*VCD*	*NIH*	*HID*
RET+	1															
RET−	0.31*	1														
SDPR	0.16	-0.36*	1													
LMV	0.19	0.09	0.06	1												
LSP	0.27	0.17	0.05	0.64*	1											
BM	-0.15	-0.04	-0.15	-0.19	-0.15	1										
LANA	-0.01	0.01	-0.05	0.49*	0.24	0.04	1									
FD	-0.01	-0.01	0.00	0.02	0.02	0.02	0.02	1								
LE	-0.10	0.12	-0.29	0.07	-0.06	0.03	0.10	0.01	1							
RAES	0.00	-0.04	0.05	-0.03	-0.02	-0.02	-0.03	0.00	0.00	1						
IPR	-0.02	-0.01	-0.03	0.24	0.08	0.01	0.15	0.02	0.08	0.01	1					
ROS	-0.03	-0.01	-0.03	-0.09	0.04	-0.14	-0.08	0.00	-0.08	0.03	-0.08	1				
NMM	-0.05	0.05	-0.16	0.5*	0.19	0.21	0.56*	0.04	0.21	-0.02	0.17	-0.12	1			
VCD	0.09	-0.09	0.24	0.11	0.06	-0.22	0.04	0.04	-0.19	0.02	-0.02	0.05	-0.01	1		
NIH	0.16	-0.13	0.35*	0.08	0.14	-0.16	-0.07	-0.01	-0.22	0.02	-0.01	0.02	-0.11	0.20	1	
HID	0.13	-0.10	0.30	-0.18	-0.01	-0.10	-0.34*	-0.01	-0.14	0.01	0.01	-0.06	-0.42*	-0.12	0.26	1

Table 2
Correlation Matrix (continued)

This table presents the correlation matrix of explanatory variables for the **second period** that contains the monthly data of IPO firms from 1995 to 2005. The asterisk highlights correlation coefficients if greater than 0.3 or less than -0.3. The total number of firm-month observations is7,174.

	RET+	*RET−*	*SDPR*	*LMV*	*LSP*	*BM*	*LANA*	*FD*	*LE*	*RAES*	*IPR*	*ROS*	*NMM*	*VCD*	*NIH*	*HID*
RET+	1															
RET−	0.32*	1														
SDPR	0.08	-0.37*	1													
LMV	0.10	0.11	-0.08	1												
LSP	0.11	0.20	-0.18	0.66*	1											
BM	-0.11	-0.07	-0.03	-0.24	-0.23	1										
LANA	0.02	-0.01	0.02	0.57*	0.32*	-0.04	1									
FD	-0.01	-0.02	0.02	-0.03	-0.02	0.04	-0.01	1								
LE	-0.05	0.14	-0.29	0.15	0.06	0.00	0.05	0.02	1							
RAES	-0.01	-0.06	0.08	-0.05	-0.06	0.02	-0.06	0.02	-0.02	1						
IPR	0.00	0.02	-0.02	0.21	0.08	-0.01	0.13	0.01	0.07	0.02	1					
ROS	-0.02	-0.01	-0.02	-0.10	0.02	-0.14	-0.06	0.02	-0.13	0.02	-0.08	1				
NMM	-0.05	0.06	-0.16	0.48*	0.19	0.17	0.45*	0.01	0.25	-0.02	0.13	-0.12	1			
VCD	0.05	-0.10	0.22	0.05	-0.07	-0.13	0.14	0.02	-0.22	0.01	-0.01	0.05	0.01	1		
NIH	0.09	-0.15	0.33*	-0.01	-0.04	-0.08	0.00	-0.01	-0.28	0.04	-0.01	0.03	-0.10	0.20	1	
HID	0.04	-0.06	0.18	-0.18	0.03	-0.07	-0.24	0.02	-0.10	0.03	0.00	-0.01	-0.42*	-0.18	0.19	1

Panel Regression Results

The method involves a random effects model as follows:

$$\begin{aligned} Y_{i,t} = {} & \beta_0 + \beta_1 RET+_{i,t-1} + \beta_2 RET-_{i,t-1} + \beta_3 SDPR_{i,t} + \beta_4 LMV_{i,t} + \beta_5 LSP_{i,t} + \\ & \beta_6 BM_{i,t} + \beta_7 LANA_{i,t} + \beta_8 FD_{i,t} + \beta_9 LE_{i,t} + \beta_{10} RAES_{i,t} + \beta_{11} IPR_{i,t} + \\ & \beta_{12} ROS_{i,t} + \beta_{13} NMM_{i,t} + \beta_{14} VCD_{i,t} + \beta_{15} NIH_{i,t} + \beta_{16} HID_{i,t} + a_i + u_{i,t} \end{aligned} \tag{1}$$

where $Y_{i,t}$ denotes each of the three liquidity variables ($RAB_{i,t}$, $TURN_{i,t}$ and $PI_{i,t}$) for IPO stock *i* in month *t*.[11] The unobservable effect, a_i, is assumed to be uncorrelated with each explanatory variable.[12] The error $u_{i,t}$ is the idiosyncratic or time-varying error.

Table 3 displays the regression results for each model specification, with Panels A, B, and C each uses a different measure of liquidity. For the ease of tracking, I discuss the results by variable category, beginning with firm visibility in this paragraph. Panel A uses the bid-ask spread as the liquidity measure. It indicates that stock visibility plays a role in explaining trading activity in the form of transaction costs, because the candidate measures of stock visibility, *LMV* and *LSP* are consistently negative and statistically significant at 1% level for periods 1 and 2, as well as the entire period. The negative effect of market value and price on transaction costs is consistent with Brennan and Hughes (1991) who suggested an inverse relation between brokerage commission and price level. The impact of book-to-market ratio is not as evident as *LMV* and *LSP* because *BM* is not significant in the first period. Panel B, in which the liquidity is measured by share turnover, shows that high price stocks as proxied by *LSP* attract more individual trading, consistent with the argument of Merton (1987).

[11] In order to have good properties in random effects estimation, the number of cross-sectional IPO sample firms is 1,497 and relatively larger than the number of time periods, 11 months.
[12] IPO firms may have unobservable effects on liquidity that are not correlated with independent variables because of volatile trading activity in the IPO aftermarket.

Table 3
Results of Random Effects Models

Table 3 summarizes the results of random effect estimations. I regress relative bid-ask (*RAB*), share turnover (*TURN*), and price impact (*PI*) on explanatory variables in Panel A, B, and C, respectively. For expositional convenience, I use subscript *t* to indicate the time period in the panel regression at the monthly frequency and omit the subscript of cross-sectional IPO firms, *i*. The signs ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A		RAB_t		
Category	Independent variable	**Full period**	**Period 1**	**Period 2**
	Constant	0.0578***	0.0524***	0.0621***
Price performance	$RET+_{t-1}$	0.0004	0.0008*	-0.0002
	$RET-_{t-1}$	-0.0014***	-0.0021***	-0.001
	$SDPR_t$	0.0117***	0.0069***	0.0101***
Stock visibility	LMV_t	-0.0051***	-0.0042***	-0.0059***
	LSP_t	-0.0048***	-0.0054***	-0.0052***
	BM_t	0.0003***	0.0001	0.0002**
Informed	$LANA_t$	-0.0019***	-0.0002	-0.0019***
Dispersion of opinion	FD_t	-0.0001	0.0003	-0.0004
	LE_t	0.0007	0.0005	0.002*
Uncertainty	$RAES_t$	0.000	0.0001	0.000
Pre-IPO uncertainty	IPR_t	0.0018***	0.0017***	0.0022***
	ROS_t	-0.0017	-0.0016	-0.0011
	NMM_t	-0.0007***	-0.0008***	-0.0004*
	VCD_t	-0.0027***	-0.0024***	-0.0029***
IPO cycle	NIH_t	0.0000	0.000	0.000*
	HID_t	0.0061***	0.007***	0.0066***
	Adj. R^2	0.4695	0.4754	0.4782

Table 3
Results of Random Effects Models (continued)

Panel B		$\boldsymbol{TURN_t}$		
Category	Independent variable	**Full period**	**Period 1**	**Period 2**
	Constant	-0.0223	0.0788**	-0.1432***
Price performance	$RET+_{t-1}$	0.0214**	0.0428***	0.0103
	$RET-_{t-1}$	0.0108	0.0177	0.0024
	$SDPR_t$	0.7102***	0.5237***	0.878***
Stock visibility	LMV_t	-0.0676***	-0.0796***	-0.0522***
	LSP_t	0.1305***	0.1402***	0.1505***
	BM_t	0.0007	0.0003	0.0008
Informed	$LANA_t$	0.0752***	0.0033	0.038***
Dispersion of opinion	FD_t	0.0119	0.0065	0.0112
	LE_t	-0.0014	0.0075	-0.0215
Uncertainty	$RAES_t$	-0.0006	-0.0003	-0.001
Pre-IPO uncertainty	IPR_t	-0.011*	-0.0125	-0.0138**
	ROS_t	0.0289	-0.0618	0.0802
	NMM_t	0.0086***	0.0235***	0.008***
	VCD_t	-0.0012	-0.0091	0.0174**
IPO cycle	NIH_t	0.0001	-0.0001	-0.0003
	HID_t	-0.0659***	-0.027***	-0.0469***
	$Adj.\ R^2$	0.2630	0.2315	0.3191

Table 3
Results of Random Effects Models (continued)

Panel C			PI_t	
Category	Independent variable	**Full period**	**Period 1**	**Period 2**
	Constant	0.0685***	0.0464***	0.0839***
Price performance	$RET+_{t-1}$	-0.0051*	-0.0017	-0.0069
	$RET-_{t-1}$	0.0099***	0.0066	0.0118**
	$SDPR_t$	0.011**	-0.0004	0.0118*
Stock visibility	LMV_t	-0.0167***	-0.0142***	-0.0185***
	LSP_t	0.0198***	0.0164***	0.0201***
	BM_t	-0.0002	-0.0002	-0.0003
Informed	$LANA_t$	-0.0038**	-0.0005	-0.0068**
Dispersion of opinion	FD_t	-0.0022	-0.0029	-0.0026
	LE_t	0.0098***	0.0066***	0.0123**
Uncertainty	$RAES_t$	-0.0001	-0.0003	-0.0004
Pre-IPO uncertainty	IPR_t	0.0027	0.0029*	0.0033
	ROS_t	0.0182	0.0656**	0.0029
	NMM_t	-0.002***	-0.0017**	-0.0016
	VCD_t	-0.0092***	-0.0045**	-0.0122***
IPO cycle	NIH_t	-0.0002**	-0.0001	-0.0003***
	HID_t	0.0076***	0.0098***	0.0087***
	$Adj.\ R^2$	0.1108	0.1294	0.1121

Note that the coefficients of LSP are opposite in Panels A and B—the implication is that higher stock price attracts more trading and lower transaction costs. Also note that the point estimates of *LSP* are twice as large as those of *LMV*, the level of stock price seems to be a more important factor on turnover than firm size. Likewise, Panel C shows that both *LMV* and *LSP* are related to price impact at 1% level. In general, I find strong evidence that proxies of stock visibility, *LMV* and *LSP*, affect trading activity in IPO aftermarket.

Among the variables of past price performance, the coefficient estimates of price volatility (*SDPR*) are positive and significant at 1% level in Panel A, suggesting that market makers increase bid-ask spreads to compensate the inventory costs and/or risk resulted from price fluctuation. The findings of *SDPR* are in agreement with previous microstructure studies such as Stoll and Whaley (1990) that found that the price volatility increases the costs of providing immediacy. Compared to other independent variables in Panel B, *SDPR* is not only statistically significant but also has a large effect across the three periods. For instance, the estimate of *SDPR*, 0.71, is higher than other explanatory variables in the full period of Panel B. This result arises possibly because the volatility of past return contributes to the portfolio rebalancing needs and thus turnover, reflecting the view of Gomes (2005) who suggested a positive correlation between trading volume and stock return volatility. On the other hand, the empirical findings of *RET+* and *RET−* are not as robust as those of *SDPR* because both coefficient estimates appear to be only marginally significant. Note, however, past returns are statistically significant in explaining spreads and turnover in Period 1 not Period 2. This result suggests that the initial period (Period 1) is driven more by momentum, compared to period 2. The difference in the two periods also means that separate analyses of initial period and later period can provide additional insights. Overall, stock visibility as measured by *LMV* and *LSP* and past return as measured by *SDPR* are consistent with the theoretical prediction regarding the role of liquidity trading.

The parameters associated with analyst coverage largely lend support for the arguments for the importance of informed agents. Panel A shows that he coefficients of analyst coverage (*LANA*) are negative at 1% level in both the entire period and period 2. The negative effect of *LANA* on trading costs implies that analyst following facilitates information and increases IPO liquidity in the secondary market. Similarly, *LANA* contributes to share turnover in Panel B as well as price impact in Panel C. The more analysts following an IPO stock, the higher is the turnover and less price impact in the aftermarket trading.

Empirical evidence hardly indicates the importance of both differences of opinion and estimation uncertainty about an IPO firm. Except for the leverage ratio in Panel C of Table 3, the coefficient estimates of analyst forecast dispersion (*FD*) and leverage (*LE*) exhibit little explanatory power on IPO trading activity. The insignificance of *RAES*, a proxy for estimation uncertainty about intrinsic value, indicates that earnings surprises for newly listed firms have no impact on trading activity as measured by *RAB*, *TURN*, and *PI*. One possible explanation is that investors are less likely to rely on earnings forecasts for IPO stocks than those for seasoned stocks because IPO firms tend to be young, tech-oriented, and equity-financed companies characterized by volatile cash flow, relative to their counterparts.

Estimation of the spectrum of parameters associated with IPO characteristics supports the relationship of post-IPO trading activity with IPO attributes. Most notable is that most of coefficient estimates of *NMM* are significant for the three dimensions of trading activity at the 1% level. Panel A shows the regression of relative bid-ask price on explanatory variables. The results suggest that the higher the number of underwriters in a syndicate (*NMM*), the lower the costs of turning around a position. Corresponding to the results in Panel A are those in Panel C based on the measurement of price impact. One additional underwriter decreases on average the absolute price change by two dollars in 1000 shares in the full period. Also in Panel B, *NMM* is positively linked to share turnover, suggesting that the lead manager, co-managers, and members of a syndicate stimulate IPO trading activity. The positive effects of underwriters on trading activity confirm the theories based on information asymmetry and/or stock visibility; that is, underwriters facilitate the resolution of information asymmetry and publicize IPO stocks, stimulating liquidity in the secondary market.

Furthermore, Table 3 shows that hot IPO dummy (*HID*) is statistically positive in Panels A and C, but negative in Panel B at 1% level. Those results are consistent with a structural break on IPO trading activity and suggest that IPO firms experience higher trading costs and price impact per share, but lower turnover from 1995 to 2000. I surmise that the shortage of supply of shares during a hot IPO period suppresses the liquidity in the IPO aftermarket. This explanation could be consistent with the findings of Ritter and Welch (2002) that share allocation issues and agency conflict matter in IPOs. .

Venture capitalists also exert an impact on post-IPO trading activity. Panel B reveals that IPO firms backed by venture capital are expected to increase turnover by 1.74% at 5% significance level, but only in period 2, namely, 6 months after the offerings. The finding is consistent with Brav and Gompers (2003) and Field and Hanka (2001) who documented the venture capitalist sales of IPO shares after the expiration of a lock-up period (typically 180 days).[13] The presence of venture capital funding (*VCD*) substantially reduces the relative bid-ask spreads and price impact in Panels A and C, respectively. Interestingly, the magnitudes of *VCD* coefficients are at least twice as large as those of *NMM*, suggesting that venture capital plays an essential role in reducing the information asymmetry and/or enhancing the visibility of IPOs.

The triviality of an overallotment option (*ROS*) indicates that an overallotment option typically exercised within the 30 days after IPO issuance date exhibits no persistent influence on *RAB*, *TURN*, and *PI*. This result justifies the hypothesis that an overallotment option plays no role in explaining IPO trading activity after the price-stabilization period. Panels A and B show that the coefficient estimates of the number of IPOs in the same industry (*NIH*) are statistically insignificant. This finding rejects the role of industry learning effects in reducing the relative bid-ask spreads and increasing turnover. Panel A shows that the coefficients of indicative price range (*IPR*) are consistently positive at 1% level. Intuitively, market makers who deal with greater estimation uncertainty about an IPO stock command higher trading premium. However, Panels B and C indicate that *IPR* is statistically insignificant, suggesting that the relationship between estimation uncertainty and IPO trading activity is ambiguous.

In short, the results of random effects model largely support theories that post-IPO trading activity depends on stock visibility, past return, informed agents, and certain IPO characteristics. The differences of opinion and estimation uncertainty about an IPO stock generate little IPO aftermarket liquidity. Nonetheless, one caveat inherent in the regression model is the contemporary causality between IPO trading activity and the spectrum of explanatory variables. I address the possible endogenous problems in the next section.

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[13] In particular, the empirical results of Brav and Gompers (2003) support the commitment hypothesis that IPO firms backed by venture capitalists are more likely to be released from the limitation of a lock-up period.

Endogeneity and Robustness Check

The specification of Equation (1) assumes the explanatory variables are exogenous, but this may not be true. For instance, one may contend that a security analyst is attracted to IPO stocks with higher trading volume and that an overallotment option is likely to be exercised in IPO stocks with more seller-initiated trades. As a consequence, the opposite causality may produce biased coefficient estimates in Equation (1). To address this issue, I substitute lagged variables for contemporaneous variables and run predictive regressions of trading activity on a broad set of one-month lagged explanatory variables. The specification of the random effects model is the following:

$$\begin{aligned} Y_{i,t} = {} & \beta_0 + \beta_1 RET+_{i,t-1} + \beta_2 RET-_{i,t-1} + \beta_3 SDPR_{i,t-1} + \beta_4 LMV_{i,t-1} + \beta_5 LSP_{i,t-1} + \\ & \beta_6 BM_{i,t-1} + \beta_7 LANA_{i,t-1} + \beta_8 FD_{i,t-1} + \beta_9 LE_{i,t-1} + \beta_{10} RAES_{i,t-1} + \beta_{11} IPR_{i,t-1} + \\ & \beta_{12} ROS_{i,t-1} + \beta_{13} NMM_{i,t-1} + \beta_{14} VCD_{i,t-1} + \beta_{15} NIH_{i,t-1} + \beta_{16} HID_{i,t-1} + a_i + u_{i,t} \end{aligned} \qquad (2)$$

where the subscript $t-1$ denotes the lag of a month; except for this time difference, the variables are as defined as those in Equation (1).

Table 4 presents the regression results from Equation (2). Stock visibility proxied by *LMV* and *LSP* calculated as of the preceding month explains the three trading measurements at 1% level. Furthermore, the findings are qualitatively similar to those in Table 3.

Table 4
Regression Results of Lagged Explanatory Variables

To address the possible heterogeneous problems, I regress contemporaneous trading activity on a broad set of one-month lagged explanatory variables. Table 4 summarizes the regression results of relative bid-ask (*RAB*), share turnover (*TURN*), and price impact (*PI*) in Panel A, B, and C, respectively. For expositional convenience, I use subscript *t* to indicate the time period at the monthly frequency and ignore the subscript of cross-sectional IPO firms, *i*. The signs ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A		RAB_t		
Category	Independent Variable	**Full period**	**Period 1**	**Period 2**
	Constant	0.0504***	0.0491***	0.0532***
Price performance	$RET+_{t-1}$	-0.0047***	-0.0027***	-0.0053***
	$RET-_{t-1}$	-0.0057***	-0.0061***	-0.0052***
	$SDPR_{t-1}$	0.0076***	0.0043***	0.0054***
Stock visibility	LMV_{t-1}	-0.0048***	-0.0045***	-0.0055***
	LSP_{t-1}	-0.0028***	-0.0031***	-0.0029***
	BM_{t-1}	0.0019***	-0.0005	0.0013***
Informed	$LANA_{t-1}$	-0.0013***	0.0003	-0.0013***
Dispersion of opinion	FD_{t-1}	-0.0003	-0.0004	-0.0005
	LE_{t-1}	0.0015***	0.0006	0.0028***
Uncertainty	$RAES_{t-1}$	0.0001*	0.0001	0.0000
Pre-IPO uncertainty	IPR_{t-1}	0.0021***	0.0012**	0.0026***
	ROS_{t-1}	-0.0016	-0.0094	-0.0034
	NMM_{t-1}	-0.0010***	-0.0008***	-0.0008***
	VCD_{t-1}	-0.0027***	-0.0024***	-0.0027***
IPO cycle	NIH_{t-1}	0.0000	0.0000	0.0000
	HID_{t-1}	0.0063***	0.0078***	0.0070***
	$Adj.\ R^2$	0.4597	0.4654	0.4704

Table 4
Regression Results of Lagged Explanatory Variables (continued)

Panel B		*TURN$_t$*		
Category	Independent variable	**Full period**	**Period 1**	**Period 2**
	Constant	0.0264	0.1048***	-0.0308
Price performance	$RET+_{t-1}$	0.0159	0.0092	0.0185
	$RET-_{t-1}$	-0.0579***	-0.0315**	-0.0674***
	$SDPR_{t-1}$	0.1031***	0.0785***	0.1084***
Stock visibility	LMV_{t-1}	-0.0485***	-0.0615***	-0.0354***
	LSP_{t-1}	0.1118***	0.1285***	0.117***
	BM_{t-1}	0.0185***	0.0141	0.0259***
Informed	$LANA_{t-1}$	0.0766***	0.0101	0.0555***
Dispersion of opinion	FD_{t-1}	0.0078	-0.0089	0.0069
	LE_{t-1}	-0.0287***	-0.0283***	-0.0683***
Uncertainty	$RAES_{t-1}$	0.0024**	0.0010	0.0033**
Pre-IPO uncertainty	IPR_{t-1}	-0.0185***	-0.0201***	-0.0205***
	ROS_{t-1}	-0.0109	-0.0998	0.0321
	NMM_{t-1}	0.0023	0.0162***	0.0011
	VCD_{t-1}	0.0300***	0.0146	0.0459***
IPO cycle	NIH_{t-1}	0.0012***	0.0008**	0.0010***
	HID_{t-1}	-0.0283***	-0.0055	-0.0118
	Adj. R^2	0.1537	0.1596	0.1660

Table 4
Regression Results of Lagged Explanatory Variables (continued)

Panel C			***PI_t***	
Category	Independent variable	**Full period**	**Period 1**	**Period 2**
	Constant	0.0765***	0.0594***	0.0846***
Price performance	$RET+_{t-1}$	-0.0041	-0.0009	-0.0066
	$RET-_{t-1}$	0.0096***	0.0094*	0.0097*
	$SDPR_{t-1}$	-0.0003	-0.0047	-0.0019
Stock visibility	LMV_{t-1}	-0.0178***	-0.0158***	-0.0187***
	LSP_{t-1}	0.0205***	0.0177***	0.0195***
	BM_{t-1}	-0.0031	-0.0035	-0.0036
Informed	$LANA_{t-1}$	-0.0037*	-0.0017	-0.0043
Dispersion of opinion	FD_{t-1}	-0.0011	-0.0002	-0.0018
	LE_{t-1}	0.0103***	0.0067**	0.0136***
Uncertainty	$RAES_{t-1}$	0.0000	0.0004	-0.0002
Pre-IPO uncertainty	IPR_{t-1}	0.0029	0.0034*	0.0031
	ROS_{t-1}	0.0260	0.0506	0.0143
	NMM_{t-1}	-0.0021**	-0.0017**	-0.0017*
	VCD_{t-1}	-0.0116***	-0.0074***	-0.0124***
IPO cycle	NIH_{t-1}	-0.0002**	0.0000	-0.0003**
	HID_{t-1}	0.0080***	0.0101***	0.0092***
	Adj. R^2	0.1153	0.1354	0.1142

Panel A of Table 4 indicates that all variables of past return are significantly related to relative bid-ask spreads at 1% level. Surprisingly, *RET*+ and *RET*− become statistically and economically significant at 1% level, relative to their counterparts in Table 3. Note that magnitude of *RET*+ and *RET*− are larger than most of other explanatory variables, the importance of *RET*+ and *RET*− is in line with the arguments of Ellis, Michaely, and O'Hara(2000) who found that market making activity of underwriters is a stand-alone profit center in the IPO aftermarket trading. Given the substantial variation and impacts of IPO returns on secondary market liquidity, underwriters are more likely to generate trading profits from a volatile and liquid IPO market, other things being equal.

The fact that *RET*+ is not significant and *RET*− is significantly negative at 1% level in Panel B seems to contradict the disposition effect, as Shefrin and Statman (1985) and Odean (1998) asserted that loss-averse investors are more likely to sell winner and keep loser; it is consistent with liquidity constraints (e.g., short-selling constraints) being more important in down markets. Consistent with Table 3, *SDPR* is significantly positive at 1% level and thus contributes to share turnover. In general, the regression results largely maintain the relationship of liquidity (or noise) trading with IPO trading activity.

Compatible with the results in Table 3, the effects of analysts following (*LANA*) on *RAB* and *TURN* are negative and positive, respectively, at 1% level in both the entire period and period 2, suggesting that the mass of informed agents helps to increase IPO liquidity in the following month. The heterogeneity of opinion as proxied by leverage (*LE*) becomes significant at 1% level in predicting IPO trading activity, whereas forecast dispersion (*FD*) remains insignificant. Nonetheless, the negative effects of *LE* on share turnover work in the opposite way as predicted by theoretical model of dispersion of opinion. Compared to other candidate variables, the coefficient estimates of relative earnings surprises (*RAES*) show a marginal impact (i.e., 0.0024 at 5% significance level in the entire period) on *TURN* in Panel B. The insignificance of *RAES* in Panels A and C also suggest a minor role of estimation uncertainty in predicting IPO aftermarket liquidity measured by *RAB* and *PI*, respectively. In brief, Table 4 confirms the findings in Table 3 that little empirical evidence supports the importance of differences of opinion and estimation uncertainty on IPO liquidity.

Turning to the results of IPO characteristics, Table 4 shows that coefficients of *NMM* and *HID* are strongly related to IPO trading activity. The negative impacts of the number of underwriters (*NMM*) on bid-ask spreads and price impact are compatible with the view of information asymmetry because a syndicate takes on the responsibility of market making and thus information production for a new issue. On the other hand, *HID* is positively associated with bid-ask spreads and price impact and is negatively related to share turnover. The fact that the presence of *HID* decreases IPO aftermarket liquidity suggests lower liquidity for newly listed firms during a hot IPO period, relative to a cold IPO period.

The presence of venture capitalists (*VCD*) adds to IPO liquidity in all three dimensions of trading activity. Nevertheless, venture capital increases share turnover only in period 2, not in the period 1. This finding may be partially explained by insider and venture capitalist-initiated orders following a lock-up period, as Brav and Gompers (2003) and Field and Hanka (2001) reported. Table 4 shows that the ratio of shares exercised in an overallotment option to total shares outstanding (*ROS*) is not significant and thus plays no essential role in forecasting IPO liquidity after the stabilization activity.

The empirical evidence of *NIH* and *IPR* are mixed. One the one hand, the number of IPOs in the same industry is related to higher turnover and lower price impact and the indicative price range is associated with lower transaction costs and turnover. On the other hand, the coefficients of *NIH* and *IPR* appear to be statistically insignificant in predicting *RAB* and *PI*, respectively. It is difficult to infer any unambiguous conclusion about the effects of *NIH* and *IPR* on IPO trading activity.

To sum up, the results are largely robust in that the results are similar to those using contemporaneous explanatory variables.

Conclusions

This paper examines the cross-sectional variations in liquidity for a sample of IPO firms from 1995 to 2005. Most of related literature focuses on the trading activity for seasoned stocks or short-term liquidity for IPO firms by using one liquidity measure. My study draws on the literature of trading activity and IPOs to analyze the determinants of IPO liquidity and sheds light on IPO trading activity from three perspectives of liquidity measures. I find that IPO liquidity is affected by the degree of past price performance, the extent of stock visibility, the mass of informed agents, and certain IPO characteristics.

The results are of interest for practitioners and academia. IPO stocks exhibits different trading behaviors from seasoned stocks. A private firm that plans to undertake an IPO arguably should consider the liquidity effect, because an illiquid market could raise the costs of capital. Market makers that earn revenues from bid-ask spreads take into account the effects of stock visibility and past price performance on IPO aftermarket trading. From a theoretical viewpoint, my finding that divergence of opinion and estimation uncertainty having little explanatory power for trading activity of IPO stocks is worthy of future research.

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Chapter 2: Does Overreaction Tend To Occur After Persistent Information in the Options Markets?

Introduction

The possible existence of investor overreaction to new information shock is an important issue for financial economists. This paper attempts to examine whether growth and value option investors react differently to periods in which persistent information occurs. By "persistent", I mean information that is similar in nature during a time period. Fro example, observing three consecutive price increases is interpreted as persistent information. In particular, I examine whether the degree of misreaction conditional on a pattern of previous information differs, if any, between growth and value investors in the options markets.

Stein (1989), Poteshman (2001), and Cao, Li, and Yu (2005) examine whether options traders overreact to information, but they do not examine the dynamic changes in the extent of overreaction.[14] It is possible that the extent of overreaction, if any, may vary over time and across different type of investors. This study exploits this possibility. I also find that reactions tend to be stronger for small stock's options than for large stock's options, consistent with the notion that the degree of information asymmetry is relatively greater for smaller stocks. The findings that the classification of investor style and the extent of prior overreaction affect subsequent overreaction perhaps motivate further theoretical development.

This study extends the evidence of multiple-day increasing overreaction as Poteshman (2001) discovers in the S&P 100 index options market by analyzing growth and value stock options separately and by examining both large and small stock index options. As Stein (1989)

[14] Stein (1989) argues that long-term S&P 100 option investors, on average, overreact to new information, compared to short-term S&P 100 option investors.

argues, testing for overreaction in the options market is less problematic than the stock market, since time-varying risk premium complicates the empirical testing on the stock market, while option value does not depend on risk premium. The implied volatility is the only salient stochastic variable in the option pricing model.

More specifically, I examine the extent of misreaction, separately for growth and value investors to a period of mostly similar information entering the options market. The growth portfolio is proxied by NASDAQ 100 index and Russell 2000 growth index while value portfolio is proxied by Russell 2000 value index. Heynen et al. (1994) estimate the degree of misprojection of long-term investors relative to short-term investors in the options market. The degree of overreaction is defined as the difference of actual and expected implied volatility dependent on stochastic volatility process, namely mean-reverting, Generalized Autoregressive Conditional Heteroscedasticity (GARCH), and Exponential GARCH (EGARCH) model. I employ the prior multiple-day overreaction as a proxy for the arrival of information shock to the options investors.

Some papers suggest that value stocks are undervalued (see Lakonishok, Shleifer, and Vishny (1994) and La Porta, Lakonishok, Shleifer, and Vishny (1997)). To the extent that this is true, value investors are likely to react strongly, after observing consecutive positive information. As a result, I expect that value investors who are subject to representative heuristic and conditional on consecutive similar information will react more strongly, compared to growth investors.

In my empirical analysis, long-term implied volatility is regressed on short-term implied volatility, stock price volatility, three-day expiration dummy on short-term options contracts, and a series of previous overreactions. The responsiveness of long-run option investors is measured by the coefficient on previous overreaction. The regression results indicate positive correlation between contemporaneous long-term implied volatility and the level of estimated overreaction in the prior period for value stocks. The correlation is negative for growth stocks. Therefore, the empirical evidence largely supports my prediction of both hypotheses above. I analyze which type of investors respond more strongly to a series of positive information. I find that value investors react more strongly to the magnitude of prior overreaction than growth investors. In addition to AR1 process, I examine whether the misreaction between growth and value investors is present under alternative specifications including GARCH and EGARCH models. The three models produce qualitatively similar results, suggesting that measurement problems are not large.

The reminder of this study is organized as follows. The next section reviews the related literature. Section 3 details hypotheses. Section 4 describes methodology and data. I present the regression results and address the robustness in Section 5. The last section concludes.

Literature Review

I summarize the literature on overreaction in the stock and options markets and then review the literature on investor styles.

Overreaction in the Stock Market

Related literature on overreaction based on stock market provides mixed evidence. Using CRSP monthly return data, De Bondt and Thaler (1985) find that investors tend to overreact to unexpected news events. One school of thoughts attributes overreaction to momentum trading, representative heuristic, overconfidence or biased self-attribution. Hong and Stein (1999) assume information asymmetry between two types of rational investors, including newswatchers and momentum traders. They theorize that stock prices underreact in the short run because of gradual informational diffusion across traders. Short-run underreaction creates arbitrage opportunities for momentum traders. However, the attempt of momentum traders to arbitrage leads to overreaction of the stocks at long horizons.

Barberis, Shleifer, and Vishny (1998) and Ritter (2003) relate representativeness bias to overreaction in the financial market. Representativeness bias is defined as underweighing long-term average, and overemphasizing on recent information. After viewing a series of similar information shocks, investors subject to representativeness bias put too much weight on such information shocks, and ignore long-run fundamental valuation. As a result, stock price is overvalued and driven above equilibrium price in case of positive information series, and vice versa. On the other hand, Fama (1998) argues that market efficiency hypothesis is still held, because most long-term return anomalies might disappear when we take the methodology problem into account. He contends that overreaction to new information occurs as frequently as underreaction.

Similar to Barberis et al. (1998) and Ritter (2003), Daniel, Hirshleifer, and Subrahmanyam (1998) account for overreaction in light of two psychology biases, overconfidence and biased self-attribution. Overconfident investors don’t respond commensurately to public information.

The level of confidence of investors also grows in the framework of the biased self-attribution. Investors tend to credit themselves for successful investment, and blame external factors for losing money. Therefore, stock price is fueled by biased self-attribution, thereby leading to overreaction in the long run.

Overreaction in the Options Market

Stein (1989), Poteshman (2001), and Cao, Li, and Yu (2005) find evidence of misreaction in the options markets. Stein assumes that stock price volatility follows autoregressive process of order one or AR1 process. In his theoretical model, investors of long-maturity options are less subject to contemporaneous information shock than those of short-term maturity options, because instantaneous volatility tends to revert to a constant long-run mean volatility. However, the empirical evidence demonstrates that implied volatility of long-maturity options and short-maturity options move almost in perfect lockstep. Stein interprets his findings as evidence for the presence of overreaction.

Poteshman (2001) investigates the response of long- and short-term option investors in periods during which a series of similar information occurs. Consistent with representativeness bias that investors are inclined to overreact through a pattern of similar information, long-term option investors overreact to periods of mostly increasing or mostly decreasing daily changes in instantaneous variance of stock return. In contrast to Stein and Poteshman, Cao, Li, and Yu (2005) conclude that investors of long-term S&P 500 index options underreact to new information contained in short-term S&P 500 index options. Moreover, they find increasing misreaction after four consecutive daily variance shocks of the same sign.

Some of empirical research cautions against evidence of overreaction in the option markets because of some methodology problems and the assumption of stochastic volatility of underlying asset return. Diz and Finucane (1993) reexamines Stein's finding by looking at changes in implied volatility, rather than levels of implied volatility for empirical testing. They find little evidence of overreaction, and indicate that a simple mean reverting model of implied volatility may not describe the time series behavior of implied volatility. Heynen, Kemna and Vorst (1994) analyze the term structure of implied volatility and find that EGARCH best describes stock volatility behavior. Consistent with market efficiency hypothesis, Cao, Li, and Yu (2005) and Harvey and Whaley (1992) find that option trading strategies based on misreaction are not profitable after taking account of transaction costs.

Investor Style

Some studies show that the classification of investor style (i.e., value and growth investors) plays a role in explaining the trading activities in response to new information shock. However, the number of empirical studies is small due to the lack of detailed data on investor trades. Rozeff and Zama (1998) find that insider purchase increases as stocks shift from growth to value categories. They interpret their evidence of insider trading as being consistent with the overreaction hypothesis that, on average, prices of value stocks tend to lie below intrinsic value, while prices of growth tend to lie above intrinsic value in the long run. Goetzmann and Massa (2002) identify classes of momentum and contrarian investors in an S&P 500 index mutual fund and study the responses of index fund investors to past daily price changes.

Hypotheses

In light of Hong and Stein (1999)'s suggestion that momentum traders lead to overreaction, I propose the momentum hypothesis that the responsiveness of value investors in the options market is an increasing function of mostly increasing or decreasing information shock, namely, persistent information shock. Suppose that prices of value stocks tend to be undervalued in the long run[15], a series of positive information are more likely to motivate buys, resulting in momentum trading and the increase of trading price. Although value investors may be aware of long-run undervaluation of value stocks, they are not sure whether value stocks are undervalued in the short run. A pattern of positive information intensifies the belief of value investors that value stocks are undervalued. As a result, a period of positive information coupled with the possibility of underpriced value stocks triggers momentum trading activities.

A smaller reaction or the reverse is likely to be true for growth stock investors. If growth securities are on average overvalued in the long run, growth investors conditional on short-run positive information shock might adopt contrarian trading activities. A period of overreaction likely moves trading price away from long-run fundamental valuation. Growth investors become suspicious of overshooting of growth stock value and they underweigh the impact of preceding overreaction on the price movement of growth securities.

In addition, I expect that firm size might play a role here. Specifically, assuming that small stocks are characterized by a greater degree of information asymmetry, price adjustments to a series of similar information should be greater for small stocks than for large stocks.

[15]See Lakonishok, Shleifer, and Vishny (1994) and La Porta, Lakonishok, Shleifer, and Vishny (1997), and Rozeff and Zaman (1998)

Rather than using the movement of options price that reflects changes in time and the price of the underlying stock, I estimate the degree of reaction of an investor by implied volatility inferred from options pricing models, because implied volatility is increasing in options price. I expect that the implied volatility of value investors increases as a pattern of mostly similar information enters the market, holding other factors constant. The next section discusses the mythology and data.

Methodology and Data

Using Cox-Ross-Rubinstein (1979) binomial option pricing model, I compute the implied volatility that accounts for the dividend yield and the possibility of early exercise for both long-term and short-term index options. $IV_{L,t}$ and $IV_{S,t}$ represent the long- and short-term implied volatility at time t, , respectively. For ease of exposition, the subscript t is omitted henceforth. Henyen et al. (1994) examine the degree of overreaction, defined as the difference between actual and expected long-term implied volatility, across three different models of stochastic volatility.[16] Let IV_{EL} denote the expected long-term implied volatility and is estimated under AR1 process in the following equations:

[16] In contrast, existing literature on stochastic volatility option pricing models focuses on a general option model that allows volatility to be stochastic. Those option pricing models rarely discuss the inference of overreaction in the option markets (e.g., Heston (1993), Bakshi, Cao, and Chen (1997), Johnson, Zuber, and Gander (2006), and Guidolin and Timmermann (2003)).

$$d\sigma_t = -\alpha(\sigma_t - \overline{\sigma})dt + \beta\sigma_t dz \tag{1}$$

$$E(\sigma_{t+j}) = \overline{\sigma} + \rho^j(\sigma_t - \overline{\sigma}) \tag{2}$$

$$IV_{EL} = \sqrt{\theta_{AR1}(IV_S^2 - \overline{\sigma}^2) + \overline{\sigma}^2} \tag{3}$$

where $\theta_{AR1} = \frac{T_2}{T_1}\frac{(\rho^{T_1} - 1)}{(\rho^{T_2} - 1)}$.

Assuming that instantaneous volatility σ_t at time *t* follows continuous-time mean-reverting AR1 process in Equation (1), the expectation of volatility at time *t+j* is given by Equation (2), where $\overline{\sigma}$ is the long-run mean level of volatility, dz is a Wiener process, and α and β are constant coefficients. ρ is the geometrically decaying parameter indicated in the AR1 process. I estimate ρ by the autocorrelation coefficient of short-term implied volatility at a one-day lag. Equation (3) shows that IV_{EL} depends on $\overline{\sigma}$, short-term implied volatility IV_S, mean-reverting parameter ρ, and the terms to expiration *T,* in which T_1 and T_2 represent the time to expiration of long- and short-term options contracts, respectively.

The second model assumes that stock return and variance follow GARCH process. GARCH (1, 1) is the most popular GARCH specification, described as follows.

$$r_t = r_f + \lambda\sigma_t + \xi_t \tag{4}$$

$$\sigma_t^{\ 2} = \alpha_0 + \alpha_1\sigma_{t-1}^{\ \ 2} + \alpha_2\xi_{t-1}$$

where r_f is the risk-free rate, and ξ_t is Gaussian white noise characterized by normal distribution $N(0,1)$. α_0, α_1, and α_2 are independent parameters to describe conditional variance σ_t^2 at time t. In case of a GARCH (1, 1), IV_{EL} is obtained as follows.

$$IV_{EL} = \sqrt{\theta_{GARCH}(IV_S^2 - \overline{\sigma}^2) + \overline{\sigma}^2} \tag{5}$$

where $\theta_{GARCH} = \frac{T_2}{T_1}\frac{\gamma^{T_1} - 1}{\gamma^{T_2} - 1}$ and $\gamma = \alpha_1 + \alpha_2$.

The third model assumes that stock return and variance follow the Exponential GARCH or EGARCH process. EGARCH (1, 1) specifies stock return and stock return volatility as follows.

$$r_t = r_f + \lambda\sigma_t + \xi_t \tag{6}$$

$$Ln\sigma_t^2 = \alpha_0 + \alpha_1 Ln\sigma_{t-1}^2 + \alpha_2\xi_{t-1} + \alpha_3(|\xi_{t-1}| - \sqrt{2/\pi})$$

where ξ_t is Gaussian white noise. α_0, α_1, and α_2 are independent parameters. One can derive the following relationship between IV_{EL} and IV_S as:

$$IV_{EL} = \sqrt{\exp[\theta_{EGARCH}(IV_S^2 - Ln\overline{\sigma}^2) + Ln\overline{\sigma}^2]} \tag{7}$$

where $\theta_{EGARCH} = \frac{T_2}{T_1}\frac{1-\alpha_1^{T_1}}{1-\alpha_1^{T_2}}$.

Poteshman (2001) tests long-horizon overreaction by regressing the difference of long-term and short-term implied volatility on instantaneous variance. The long-term implied volatility is implicitly a function of short-term implied volatility and instantaneous variance. He uses the cumulative sign and level of previous unexpected changes in instantaneous variance as a proxy for information to options traders. Largely following his approach, to test whether the cumulative *sign* of previous overreaction affect current response of long-term options investors, I construct the following two equations:

$$IV_L = \beta_1 IV_S + \beta_2 V + \beta_3 D + \delta_1 SPO \tag{8}$$

$$SPO = \sum_{i=1}^{w} \text{sign}(IV_L - IV_{EL})_{t-i} \tag{9}$$

where IV_L indicates the implied volatility of long-term options investors and V represents the stock price volatility. D is a dummy variable that takes on the value of one if the time to expiration of short-term options is equal to or less than three days, and zero otherwise. SPO is a measure of previous overreaction over a window of w trading dates and defined as the cumulative *sign* of the difference between expected and actual long-term implied volatility from trade date $t - w$ to trade date $t - 1$.

In addition to testing the cumulative sign of previous overreaction, I investigate the impact of cumulative *level* of previous overreaction (LPO) on the long-term implied volatility as follows:

$$IV_L = \beta_1 IV_S + \beta_2 V + \beta_3 D + \delta_2 LPO \tag{10}$$

$$LPO = \sum_{i=1}^{w} (IV_L - IV_{EL})_{t-i} \tag{11}$$

where *LPO* is the second measure of previous overreaction over a window of *w* trading dates and defined as the cumulative *level* of the difference between expected and actual long-term implied volatility from trade date $t - w$ to trade date $t - 1$.

As discussed earlier, I expect that, for value stock options, the coefficient on *SPO* and *LPO* is positive and larger than that of growth stock options.

Daily options data from 2003 to 2005 are obtained by Chicago Board Options Exchange (CBOE), which provides open price, close price, high and low prices, bid and ask prices, expiration date, open interest, and trading volume for both call and put contracts. I use options on NASDAQ 100 index and Russell 2000 growth index to represent growth portfolios, while options on Russell 2000 value index to proxy for value portfolios. Each of the index options data is dividend into two subset, calls and puts. The rationale to separate the analyses of puts and puts is that generally trading in puts is heavier than calls. If liquidity affects pricing and thus implied volatility, pooling calls and puts can produce misleading results.

Following the conventional data treatment, I limit observations to near-the-money option in which stock price is in the range of 10 percent of strike price. As in Stein (1989), I categorize the short-term options contracts with equal to or less than one-month maturity, and long-term options contracts with more than one-month maturity. Stock price and dividend yield are extracted from the Center for Research in Security Prices (CRSP), and risk-free interest rate is obtained from the website of St. Louis Federal Reserve Bank.

Table 1 presents the summary statistics of implied volatility. Generally speaking, the level of long-term implied volatility is higher than that of short-term implied volatility for three index options, suggesting some degree of market segmentation. The implied volatility of NASDAQ

100 index and Russell 2000 growth index is higher than that of Russell 2000 value index, irrespective of the short-term or long-term options. Higher implied volatility of growth portfolios is consistent with the notion that growth portfolios are perceived as being more risky and volatile than value portfolios.

Regression Results and Robustness Check

I examine the effects of prior five-day overreaction (w=5) on current reaction of investors. Under the assumption of AR1 stochastic volatility process, Table 2 shows the regression results of equations (8) and (10) in Panels A and B, respectively. Both Panels A and B indicate positive coefficients on *SPO* and *LPO* for the Russell 2000 value index option and statistically significant at 1% level, regardless of call and put options. This finding is consistent with my expectation that value investors will react strongly to a pattern of similar information, as measured by the degree of overreaction over a window of the previous five trade dates. Panel B shows that the coefficients on *LPO* for NASDAQ 100 investors are negative and statistically significant at 1% level. This finding suggests that growth investors tend to underreact to a pattern of similar information. Holding other factors fixed, the 1% increase of prior overreaction lowers the subsequent implied volatility by 0.02% for NASDAQ 100 investors. Table 2 also shows the results of the Chow test conducted between the value and growth indices. The F statistics indicates that the joint hypothesis that all of regression coefficients are equal between the value and growth indices is rejected at 1% level. The evidence of structural difference suggests that growth and value investors respond differently to the previous overreaction.

Table 1
Summary Statistics of Implied Volatility

This table shows the mean, median and standard deviation of implied volatility based on Cox-Ross-Rubinstein (1979) binomial option pricing model. Daily options data from 2003 to 2005 are obtained by Chicago Board Options Exchange (CBOE). Each of the index options data is dividend into two subset, calls and puts. Following the conventional data treatment, I limit observations to near-the-money option in which stock price falls into 10 percent of strike price. The number of daily observations is 756.

		Implied volatility	
	Mean	**Median**	**Standard deviation**
CALL OPTIONS			
Russell 2000 Value			
Short-term	0.1794	0.1756	0.04080
Long-term	0.1905	0.1908	0.02542
Russell 2000 Growth			
Short-term	0.2241	0.2127	0.0706
Long-term	0.2291	0.2275	0.0330
NASDAQ 100			
Short-term	0.2101	0.1951	0.0729
Long-term	0.2357	0.2231	0.0631
PUT OPTIONS			
Russell 2000 Value			
Short-term	0.1825	0.1773	0.0433
Long-term	0.1919	0.1903	0.0249
Russell 2000 Growth			
Short-term	0.2264	0.2158	0.0628
Long-term	0.2350	0.2336	0.0306
NASDAQ 100			
Short-term	0.2155	0.2007	0.0727
Long-term	0.2366	0.2247	0.0627

The magnitude and sign of δ_2 among three types of investors are of interest. Panel B of Table 2 displays that the size of δ_2 for Russell 2000 growth index is in between those of Russell 2000 value and NASDAQ 100 index, and the coefficient is negative for NASDAQ. This suggests the following: Facing a series of similar information, traders in Russell 2000 value, which represents small value stocks, react most strongly in terms of their adjustments in implied volatility. The reaction is weaker for small growth stocks, proxied by Russell 2000 growth. Investors in large growth stocks NASDAQ, on the other hand, tend to underreact. Overall, these results are consistent with my expectations.

Panel A of Table 2 displays that δ_1 is significant only at 10% level for NASDAQ 100 put options investors and insignificant for NASDAQ 100 call options investors. The magnitude of δ_1 is very close to zero, suggesting that NASDAQ 100 investors are indifferent in the cumulative sign of previous five-day overreaction. One possible explanation for the neutrality of NASDAQ 100 index to prior information is the firm size effect. Specifically, investors in larger, more liquid markets are less prone to overreactions.

Turning to the pair of Russell 2000 growth and value index in Panel A, Russell 2000 growth investors react more strongly than Russell 2000 value investors in response to the cumulative sign of previous five-day overreaction because of higher and statistically significant δ_1. However, I cautiously point out that the δ_1 for both investors is small. Given one additional positive sign of prior overreaction, the difference of current overreaction between Russell 2000 growth and value index is only 0.0007 for both call and put options. Table 1 indicates that the average long-term implied volatilities of Russell 2000 growth index are 0.2291 and 0.2350 for call and put options, respectively. The size of 0.0007 conditional on an additional sign of prior overreaction suggests that Russell 2000 growth investors on average react more by only 0.3 percent than Russell 2000 value investors. However, the issue of ordinal information contained in the *SPO* may complicate the interpretation of slightly higher overreaction of Russell 2000 growth index, compared to Russell 2000 value index. Because *SPO* is a nonparametric and ordinal variable, the difference between a *SPO* of four and of three might not be the same as the difference between a *SPO* of two and of one. In sum, Panel B of Table 2 suggests that value investors react more strongly than growth investors in the magnitude of prior overreaction, whereas Panel A of Table 2 suggests that Russell 2000 growth investors react slightly higher than Russell 2000 value investors in terms of the cumulative sign of prior overreaction.

As a robustness check, I use GARCH (1, 1) and EGARCH (1, 1) model to compute *SPO* and *LPO* contained in a pattern of previous information over a window of five trade dates. Appendix shows the parameters associated with GARCH (1, 1) and EGARCH (1, 1) models. Tables 4 and 5 show the regression results under the assumption of GARCH (1, 1) and EGARCH (1, 1), respectively. Because δ_2 are statistically positive for Russell 2000 value index and negative for NASDAQ 100 index at 1% level, and δ_1 of Russell 2000 growth index is higher than that of Russell 2000 value index, the empirical evidence presented in Table 4 and 5 is quantitatively similar to that in Table 3. Overall, I conclude that the results are robust to different specifications of stochastic volatility process, especially for a pattern of previous five-day overreaction measured in levels.

Table 2
Regression Results of AR1 stochastic volatility process

This table shows the results of equation (8), assuming AR1 stochastic volatility process. Long-term implied volatility (IV_L) is regression on short-term implied volatility (IV_S), stock price volatility (V), short-term expiration dummy (D), and the cumulative sign of previous five-day overreaction (SPO). D takes on the value of one if the time to expiration of short-term options is equal to or less than three days, and otherwise zero. The signs ***, **, * represents significance at 1%, 5%, and 10% level. The Chow test is conducted between two pairs. The first pair consists of Russell 2000 Value and Growth index option, and the second one consists of Russell 2000 Value and NASDAQ 100 index option. The F statistics of each pair is shown in the columns of Russell 2000 Growth index and NASDAQ 100 index, respectively.

Panel A	$IV_L=\beta_1 IV_S+\beta_2 V+\beta_3 D+\delta_1 SPO$		
CALL OPTIONS	**Russell 2000 Value**	**Russell 2000 Growth**	**NASDAQ 100**
β_1	0.3680***	0.2846***	0.4917***
β_2	0.7213***	0.7997***	0.6839***
β_3	0.0064***	-0.0102***	0.0133***
δ_1	0.0013***	0.0020***	-0.0001
R^2	0.9904	0.9839	0.9890
Chow test F statistic		8.60***	41.04***
PUT OPTIONS	**Russell 2000 Value**	**Russell 2000 Growth**	**NASDAQ 100**
β_1	0.3321***	0.2792***	0.4139***
β_2	0.7388***	0.8025***	0.7787***
β_3	0.0036	-0.0061*	0.0016***
δ_1	0.0023***	0.0030***	-0.0005*
R^2	0.9899	0.9854	0.9890
Chow test F statistic		4.7***	40.87***

Table 2 (Continued)
Regression Results of AR1 stochastic volatility process

This table shows the results of equation (10), assuming AR1 stochastic volatility process. Long-term implied volatility (IV_L) is regression on short-term implied volatility (IV_S), stock price volatility (V), short-term expiration dummy (D), and the cumulative level of previous five-day overreaction (LPO). D takes on the value of one if the time to expiration of short-term options is equal to or less than three days, and otherwise zero. The signs ***, **, * represents significance at 1%, 5%, and 10% level. The Chow test is conducted between two pairs. The first pair consists of Russell 2000 Value and Growth index option, and the second one consists of Russell 2000 Value and NASDAQ 100 index option. The F statistics of each pair is shown in the columns of Russell 2000 Growth index and NASDAQ 100 index, respectively.

Panel B	$IV_L=\beta_1 IV_S+\beta_2 V+\beta_3 D+\delta_2 LPO$		
CALL OPTIONS	**Russell 2000 Value**	**Russell 2000 Growth**	**NASDAQ 100**
β_1	0.3439***	0.2719***	0.5122***
β_2	0.7143***	0.8124***	0.6987***
β_3	0.0057***	-0.0099***	0.0125***
δ_2	0.0844***	0.0498***	-0.279***
R^2	0.9915	0.9838	0.9895
Chow test F statistic		9.99***	70.81***
PUT OPTIONS	**Russell 2000 Value**	**Russell 2000 Growth**	**NASDAQ 100**
β_1	0.3017***	0.2695***	0.4221***
β_2	0.7583***	0.8366***	0.7920***
β_3	0.036*	-0.0074**	0.0010
δ_2	0.0887***	0.0469***	-0.0216***
R^2	0.9908	0.9851	0.9893
Chow test F statistic		5.73***	60.61***

Table 3
Regression Results of GARCH (1, 1) stochastic volatility process

This table shows the results of equation (8), assuming GARCH (1, 1) stochastic volatility process. Long-term implied volatility (IV_L) is regression on short-term implied volatility (IV_S), stock price volatility (V), short-term expiration dummy (D), and the cumulative sign of previous five-day overreaction (SPO). D takes on the value of one if the time to expiration of short-term options is equal to or less than three days, and otherwise zero. The signs ***, **, * represents significance at 1%, 5%, and 10% level. The Chow test is conducted between two pairs. The first pair consists of Russell 2000 Value and Growth index option, and the second one consists of Russell 2000 Value and NASDAQ 100 index option. The F statistics of each pair is shown in the columns of Russell 2000 Growth index and NASDAQ 100 index, respectively.

Panel A	$IV_L=\beta_1 IV_S+\beta_2 V+\beta_3 D+\delta_1 SPO$		
CALL OPTIONS	**Russell 2000 Value**	**Russell 2000 Growth**	**NASDAQ 100**
β_1	0.3682***	0.2846***	0.4887***
β_2	0.7205***	0.8000***	0.6593***
β_3	0.0064***	-0.0103***	0.0142***
δ_1	0.0013***	0.0020***	0.0014***
R^2	0.9904	0.9839	0.9892
Chow test F statistic		8.54***	40.56***
PUT OPTIONS	**Russell 2000 Value**	**Russell 2000 Growth**	**NASDAQ 100**
β_1	0.3327***	0.2823***	0.4169***
β_2	0.7340***	0.7978***	0.7636***
β_3	0.0033	-0.0061*	0.0025
δ_1	0.0024***	0.0030***	0.0002
R^2	0.9900	0.9855	0.9890
Chow test F statistic		4.48***	39.54***

Table 3 (Continued)
Regression Results of GARCH (1, 1) stochastic volatility process

This table shows the results of equation (10), assuming GARCH (1, 1) stochastic volatility process. Long-term implied volatility (IV_L) is regression on short-term implied volatility (IV_S), stock price volatility (V), short-term expiration dummy (D), and the cumulative level of previous five-day overreaction (LPO). D takes on the value of one if the time to expiration of short-term options is equal to or less than three days, and otherwise zero. The signs ***, **, * represents significance at 1%, 5%, and 10% level. The Chow test is conducted between two pairs. The first pair consists of Russell 2000 Value and Growth index option, and the second one consists of Russell 2000 Value and NASDAQ 100 index option. The F statistics of each pair is shown in the columns of Russell 2000 Growth index and NASDAQ 100 index, respectively.

Panel B	$IV_L=\beta_1 IV_S+\beta_2 V+\beta_3 D+\delta_2 LPO$		
CALL OPTIONS	**Russell 2000 Value**	**Russell 2000 Growth**	**NASDAQ 100**
β_1	0.3441***	0.2725***	0.5040***
β_2	0.7140***	0.8101***	0.6992***
β_3	0.0057***	-0.0098***	0.0130***
δ_2	0.0846***	0.0529***	-0.0249***
R^2	0.9915	0.9839	0.9893
Chow test F statistic		9.47***	61.31***
PUT OPTIONS	**Russell 2000 Value**	**Russell 2000 Growth**	**NASDAQ 100**
β_1	0.3030***	0.2695***	0.4174***
β_2	0.7572***	0.8339***	0.7870***
β_3	0.0036*	-0.0073**	0.0015
δ_2	0.0887***	0.0505***	-0.0170***
R^2	0.9909	0.9852	0.9892
Chow test F statistic		5.29***	53.15***

Table 4
Regression Results of EGARCH (1, 1) stochastic volatility process

This table shows the results of equation (8), assuming EGARCH (1, 1) stochastic volatility process. Long-term implied volatility (IV_L) is regression on short-term implied volatility (IV_S), stock price volatility (V), short-term expiration dummy (D), and the cumulative sign of previous five-day overreaction (SPO). D takes on the value of one if the time to expiration of short-term options is equal to or less than three days, and otherwise zero. The signs ***, **, * represents significance at 1%, 5%, and 10% level. The Chow test is conducted between two pairs. The first pair consists of Russell 2000 Value and Growth index option, and the second one consists of Russell 2000 Value and NASDAQ 100 index option. The F statistics of each pair is shown in the columns of Russell 2000 Growth index and NASDAQ 100 index, respectively.

Panel A	$IV_L = \beta_1 IV_S + \beta_2 V + \beta_3 D + \delta_1 SPO$		
CALL OPTIONS	**Russell 2000 Value**	**Russell 2000 Growth**	**NASDAQ 100**
β_1	0.3690***	0.2834***	0.4900***
β_2	0.7188***	0.7993***	0.6718***
β_3	0.0066***	-0.0102***	0.0138***
δ_1	0.0013***	0.0020***	0.0007*
R^2	0.9904	0.9840	0.9891
Chow test F statistic		8.84***	40.20***
PUT OPTIONS	**Russell 2000 Value**	**Russell 2000 Growth**	**NASDAQ 100**
β_1	0.3347***	0.2761***	0.4158***
β_2	0.7233***	0.7868***	0.7672***
β_3	0.0031	-0.0057*	0.0024
δ_1	0.0028***	0.0037***	0.0001
R^2	0.9902	0.9856	0.9890
Chow test F statistic		5.10***	42.33**

Table 4 (Continued)
Regression Results of EGARCH (1, 1) stochastic volatility process

This table shows the results of equation (10), assuming EGARCH (1, 1) stochastic volatility process. Long-term implied volatility (IV_L) is regression on short-term implied volatility (IV_S), stock price volatility (V), short-term expiration dummy (D), and the cumulative level of previous five-day overreaction (LPO). D takes on the value of one if the time to expiration of short-term options is equal to or less than three days, and otherwise zero. The signs ***, **, * represents significance at 1%, 5%, and 10% level. The Chow test is conducted between two pairs. The first pair consists of Russell 2000 Value and Growth index option, and the second one consists of Russell 2000 Value and NASDAQ 100 index option. The F statistics of each pair is shown in the columns of Russell 2000 Growth index and NASDAQ 100 index, respectively.

Panel B	$IV_L = \beta_1 IV_S + \beta_2 V + \beta_3 D + \delta_2 LPO$		
CALL OPTIONS	**Russell 2000 Value**	**Russell 2000 Growth**	**NASDAQ 100**
β_1	0.3430***	0.2681***	0.5137***
β_2	0.7118***	0.8124***	0.6966***
β_3	0.0058***	-0.0097**	0.0126***
δ_2	0.0858***	0.0522***	-0.0267***
R^2	0.9915	0.9839	0.9894
Chow test F statistic		10.31***	69.28***
PUT OPTIONS	**Russell 2000 Value**	**Russell 2000 Growth**	**NASDAQ 100**
β_1	0.3002***	0.2667***	0.4224***
β_2	0.7552***	0.8361***	0.7900***
β_3	0.0037*	-0.0073**	0.0010
δ_2	0.0919***	0.0488***	-0.0201***
R^2	0.9910	0.9851	0.9893
Chow test F statistic		6.03***	60.39***

Conclusions

This paper examines the option market's reaction to a series of preceding information shocks or overreactions, as measured by the difference of actual and expected long-term implied volatility over a window of five trade dates. Comparing the reactions between growth and value investors in the options market reduces, to some extent, the methodology problem and measurement error in testing for overreaction in the stock market. The findings mostly support my expectation that, after observing a series of similar information, value investors react more strongly than growth investors in the level of prior overreaction. Moreover, I find small stocks' reactions are stronger than those of large stocks, consistent with information asymmetry being relatively more important for small stocks.

In terms of the sign of prior overreaction, I find the opposite result: higher overreaction of Russell 2000 growth investors relative to Russell 2000 value. Whether investors perceive the sign and magnitude of prior overreaction as different sets of information deserves further analysis. Furthermore, the evidence shows that overreaction is statistically significant, but the degree of overreaction may be small in economic magnitude, factoring in transaction costs. An interesting question for future research is whether arbitrage opportunities exist after taking into account the substantial bid-ask spread in the options market.

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Appendix A

Parameter Estimates under GARCH (1, 1)

Russell 2000 Value

	Coefficient	Standard Error
λ	-3.725***	0.045
α_0	0.000	0.000
α_1	0.079	0.054
α_2	0.641**	0.314
$\gamma=\alpha_1+\alpha_2$	0.720	
AIC	-4498	

Russell 2000 Growth

	Coefficient	Standard Error
λ	-3.085***	0.045
α_0	0.000	0.000
α_1	0.053	0.042
α_2	0.753***	0.259
$\gamma=\alpha_1+\alpha_2$	0.806	
AIC	-4214	

NASDAQ 100

	Coefficient	Standard Error
λ	-3.396***	0.056
α_0	0.000**	0.000
α_1	0.106***	0.031
α_2	0.869***	0.032
$\gamma=\alpha_1+\alpha_2$	0.975	
AIC	-4039	

Appendix B
Parameter Estimates under EGARCH (1, 1)

Russell 2000 Value

	Coefficient	**Standard Error**
λ	-3.676***	0.045
α_0	-1.477	1.229
$\gamma=\alpha_1$	0.833***	0.139
α_2	-0.058*	0.033
α_3	0.117	0.080
AIC	-4502	

Russell 2000 Growth

	Coefficient	**Standard Error**
λ	-3.024***	0.043
α_0	-1.446	1.254
$\gamma=\alpha_1$	0.830***	0.148
α_2	-0.052	0.035
α_3	0.088*	0.082
AIC	-4218	

NASDAQ 100

	Coefficient	**Standard Error**
λ	-3.375***	0.055
α_0	-0.416*	0.217
$\gamma=\alpha_1$	0.950***	0.026
α_2	0.015	0.021
α_3	0.259***	0.062
AIC	-4035	

Vita

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